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Data Assimilation Improves Estimates of Climate-Sensitive Seasonal Snow

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Abstract
As the Earth warms, the spatial and temporal response of seasonal snow remains uncertain. The global snow science community estimates snow cover and mass with information from land surface models, numerical weather prediction, satellite observations, surface measurements, and combinations thereof. Accurate estimation of snow at the spatial and temporal scales over which snow varies has historically been challenged by the complexity of land cover and terrain and the large global extent of snow-covered regions. Like many Earth science disciplines, snow science is in an era of rapid advances as remote sensing products and models continue to gain granularity and physical fidelity. Despite clear progress, the snow science community continues to face challenges related to the accuracy of seasonal snow estimation. Namely, advances in snow modeling remain limited by uncertainties in modeling parameterization schemes and input forcings, and advances in remote sensing techniques remain limited by temporal, spatial, and technical constraints on the variables that can be observed. Accurate monitoring and modeling of snow improves our ability to assess Earth system conditions, trends, and future projections while serving highly valued global interests in water supply and weather forecasts. Thus, there is a fundamental need to understand and improve the errors and uncertainties associated with estimates of snow. A potential method to overcome model and observational shortcomings is data assimilation, which leverages the information content in both observations and models while minimizing their limitations due to uncertainty. This article proposes data assimilation as a way to reduce uncertainties in the characterization of seasonal snow changes and reviews current modeling, remote sensing, and data assimilation techniques applied to the estimation of seasonal snow. Finally, remaining challenges for seasonal snow estimation are discussed.

Keywords Data assimilation · Seasonal snow · Remote sensing of snow · Modeling of snow · Climate change

Introduction and Motivations

For many regions of the world, seasonal snow acts as a “virtual” reservoir that accumulates in the winter and melts in spring, storing and subsequently providing water for urban and agricultural users [166]. About 15% of the world’s population derives the majority of its water supply from seasonal snowpack [7]. Snow also presents hazards such as flood and avalanche risks, disruption to transportation, and impacts on livestock, wildlife, and infrastructure [10, 31, 39, 116, 117, 138, 157]. In addition, snow-cover strongly influences weather and climate. The highly reflective, emissive, and insulative properties of snow compared with other surfaces alter the heat and moisture fluxes between the land and the atmosphere [65, 165]. The feedback effects of snow on atmospheric circulation and downstream weather patterns can have inter-continental impacts. For example, anomalous snow cover conditions in Siberia strongly influence North American weather [28, 47, 74] and spring snow cover in the Himalaya can affect the formation of the Indian monsoon [144, 170, 171]. Accurate representation of snow cover in models can improve the skill of numerical weather prediction and water resource management. Snow estimation is “a trillion-dollar science question” [153] that is increasingly important as global warming forces substantial change.

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Declines in snow-covered area and volume, and shifts to earlier snow disappearance, have been observed across the Northern Hemisphere since many satellite records began [17, 38, 54, 72, 121]. To date, snow loss attributed to warming temperatures has primarily occurred in spring and at the geographic margins of historical seasonal snow cover, namely at mid-latitudes and lower elevations [72, 113, 129]. Snow cover reductions in response to warming impact the Earth system via complex feedbacks that are best addressed using models. For example, while warming is accelerating the global hydrologic cycle [79], snowmelt rates may be slower in a warmer world due to less snow persisting into the warmest months [115]. Similarly, Arctic warming will degrade permafrost [91], yet shallower snow provides less insulation of soils from winter air temperatures, resulting in colder soils in a warmer world [66]. Accurate monitoring and modeling of snow improves inclusion of these process interactions in future Earth system projections while also serving highly valued global interests in water supply, weather forecasts, and agriculture [153].

While spring snow cover reductions are evident in satellite records [13], station observations [87, 113], and global model reanalysis [140, 169], there remains much variability and uncertainty in the spatial and seasonal patterns. For example, increasing autumn snow cover trends in the Northern Hemisphere, especially at Eurasian high latitudes, have been attributed to seasonal precipitation increases (e.g., [2, 75]). Several studies have questioned this positive trend, arguing that it is inconsistent with North American autumn surface temperature warming trends (e.g., [14, 75]). Similarly, while there is a general consensus that snow volume and mass over the terrestrial Arctic is decreasing, the literature has reported highly variable regional trends [17]. The limited unanimity on how global snow patterns have changed is likely due the lack of comprehensive and accurate snow estimates from models and/or remote sensing observations. There is a critical need to improve snow estimates in reanalysis products, operational models, and future climate projections.

Modeling and remote sensing approaches have inherent uncertainties and limitations [57]. Uncertainties in models are mainly associated with their physics and parameterization schemes or error-prone input forcings such as precipitation, temperature, and windspeed [114, 131]. Model errors can be reduced with careful configuration. For example, when run at sufficiently high grid spacing, a properly parameterized regional climate model can resolve orographic precipitation fields better than observation networks [102]. Similarly, remote sensing techniques have inherent limitations due to temporal, spatial, and technical constraints on critical snow variables. Careful assessment and model process representation are required to represent global snow patterns and to disentangle the relative contributions of internal climate variability and anthropogenic forcing.

Simulating and observing fine-scale spatial and temporal seasonal snow-cover patterns have historically been challenged by a high degree of environmental complexity and limited in situ observations [128]. Important advances by the snow science community allow us to better understand the role and interactions of snow in Earth systems. These advances are possible as remote sensing products and models continue to increase in granularity and physical fidelity [25]. Nonetheless, there remain fundamental knowledge gaps. A critical area is the need to document and narrow the uncertainties in snow estimates [17] from observations and modeling.

A promising method to alleviate shortcomings in snow models and observations and to improve our ability to monitor changes in seasonal snow is data assimilation (e.g., [4, 59, 77, 156]b). Data assimilation combines existing and emerging observations (both in situ and satellite observations) with model estimates, thus bridging scale and limitation gaps between observations and models. Data assimilation can integrate measurements from multiple sensors to improve model estimates of snow properties including mass, commonly referred to as snow water equivalent (SWE). Thus, data assimilation offers the potential to document and reduce uncertainties in snow representation. We argue that only through the assimilation of ground observations and model data can satellite-derived snow depth and SWE fields reach the accuracy level required by the current user community including climatologists, hydrologists, and weather and climate forecasters [162].

The purpose of this article is to review current techniques used to estimate seasonal snow and to elucidate outstanding challenges that could be addressed by combining model estimates with remotely sensed observations. The first two sections report the key benefits and limitations of remote sensing and modeling of seasonal snow. The third section presents the concept of data assimilation. Finally, section four provides a brief summary and conclusions of the current techniques for estimating seasonal snow.

Snow Modeling

A half-century of thorough inquiry has established numerical representations of the effects of wind (e.g., [142]), topography (e.g., [108]), and vegetation (e.g., [64]) on snow distribution. However, the complex relationships between these variables and their high variability in time and space and at different scales continue to challenge snow model predictive skill [83]. Despite these challenges, the need for accurate predictions of snow water resources has prompted the development of operational numerical snow models for a range of applications including hydrological forecasting (e.g., [3]), weather prediction (e.g., [120]), avalanche forecasting (e.g., [92]), climate modeling (e.g., [12]), and retrieval of snow characteristics by remote sensing (e.g., [107]). Snow models differ in their degree of process representation depending on the intended application [49, 159]. In this regard, snow models fall into two general categories: temperature index models and energy balance models.

Temperature index models use empirical relationships between local air temperature and snowmelt to estimate snow depletion [123]. Although limited in their representations of physical processes, such models have often been used in hydrological forecasting and climate impact studies. Energy balance snow models, on the other hand, are designed to simulate all energy fluxes into and out of a snowpack and are used to predict snowmelt as a result of the computed net internal energy. These process-based models have been shown to yield improved local SWE estimates over temperature index methods [167]. Even within general snow model categories, models differ in their representation of snowpack stratigraphy and vary from single-layer (e.g., [50, 141]), to three-layer (e.g., [155]), to detailed multilayer (e.g., [18, 82]) snowpack representations. Detailed knowledge of the internal snowpack structure is critical for radiative transfer applications in remote sensing [168] and avalanche forecasts [92] and has utility in hydrological and climate change sensitivity applications [9], presumably due to the correlation between snow material structure and surface–atmosphere interactions.

Physically based snow energy balance models permit the assessment of how snow properties such as density, albedo, emissivity, and conductivity may impact other environmental processes and states. However, their estimates rely on accurate representation of snow physics and input forcings such as precipitation, temperature, and windspeed [114, 131]. That is, snow model estimates remain hindered by uncertain forcing (e.g., meteorological conditions) and weaknesses in the snow model, associated with both the fidelity of the equations used to simulate snow processes (structural uncertainty) and the parameter values selected for use in the model equations [150]. In the case of high uncertainty, simple snow models can be a viable alternative to physically based energy balance models; however, the latter offer more flexibility to benefit from the increasing availability and performance of satellite remote sensing techniques ("Snow Modeling" section) to validate prognostic model states that simpler models may not track (e.g., surface temperature; [70]). The process-based models are often better structured to improve state estimates through data assimilation ("Remote Sensing of Seasonal Snow" section).

Over the past decade, much progress has been made on the evaluation of snow in models, in particular through the Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) [149] and the Snow Model Intercomparison Project (SnowMIP) [51]. This progress has recently been extended to snow modules of global land surface schemes in the Earth system Model (ESM) SnowMIP [89]. Despite decades of marked model improvements, the comment by Dirmeyer et al. [41] still holds that "Generally there is mediocre agreement among the models for most of the snow-related variables, suggesting a potential area of continuing weakness in global land surface schemes." Model uncertainty remains a persistent gap in snow estimation. Clear avenues for improvement are (1) better characterized sources of model uncertainty and 2) improved model structure, forcing data, and algorithms to reduce that uncertainty. The assimilation of remotely sensed and in situ observations could address these points by characterizing forcing errors (e.g., snowfall precipitation; [100]) and by improving model parameterization (e.g., snow albedo; [119]) while tracking and reducing the inherent uncertainty in the system.

Remote Sensing of Seasonal Snow

Advances in satellite remote sensing systems continue to revolutionize the way we monitor snow. New generations of sensors and platforms now provide more extensive and global coverage of mountainous regions where seasonal snow accumulates [57, 143]. To date, however, no satellite mission dedicated to the estimation of snow water equivalent exists. International community efforts such as NASA's SnowEx [86] and the Nordic Snow Radar Experiment [94] aim to better characterize sensor performance and to identify optimum multi-sensor synergies to map critical snowpack properties in future satellite missions.

Due to the nature of interactions between snow cover and electromagnetic radiation of different frequencies, snow can be distinguished from other terrestrial surfaces using satellite observations with various active and passive sensor techniques. Active sensors provide their own source of energy and illumination to the observed objects and the remote sensor detects the return illumination or energy that is backscattered from the target object. Active remote sensing technologies that have been used for estimating seasonal snow include active microwave and light detection and ranging (lidar) techniques. Passive sensors detect the naturally emitted radiation from the Earth surface. The most common passive remote sensing techniques for snow are visible and near-infrared observations (e.g., [27, 133], Section 2.1) and passive microwave detection (e.g., [53, 96], Section 2.2). Furthermore, airborne gamma radiation measurements detect the natural terrestrial gamma radiation emitted from potassium, uranium, and thorium radioisotopes in the upper layer of soil. By measuring the difference in gamma radiation before and after the snow falls, these measurements can be used to estimate snowpack mass [20, 22]. In general, active sensors offer higher spatial resolutions than passive ones but at the expense of longer repeat times, which can limit the frequency of global coverage.

The spectral properties of snow depend upon several factors including grain size and shape, water content, impurity concentrations, temperature, and depth (e.g., [40, 42, 147]). Snow remote sensing techniques have primarily focused on estimating three key variables of seasonal snow: (1) snow extent, (2) snow depth, and (3) SWE. The snow extent is the surface area that is covered by snow, while depth and SWE provide estimates of snow volume and mass, respectively. Snow extent is generally obtained reliably with high spatial and temporal resolution from visible and near-infrared data (e.g., [69, 124, 136]), but sensors retrieving snow depth, such as the Advanced Topographic Laser Altimeter System (ATLAS) on ICESat-2 [67], are generally limited in spatial coverage. Comparatively, there is far less confidence in the measurement of SWE [26, 86].

Visible Near-Infrared Observations

In the visible and near-infrared (Vis/NIR) part of the electromagnetic spectrum, snow is highly reflective; satellite sensors measuring in this part of the spectrum can be used to identify the presence or absence of snow. Vis/NIR observations have been used to detect snow cover since the mid-1960s. In particular, Vis/NIR observations can provide regional to global estimates of fractional snow-covered extent or area [30, 124, 139]. Vis/NIR data is often available at spatial resolutions ranging from tens to hundreds of meters with varying temporal resolution (daily to every couple of weeks). These resolutions are generally considered acceptable for the mapping of snow patterns and changes, even in complex mountainous regions [72]. Table 1 reports some of the key Vis/NIR missions targeted to seasonal snow estimation. Examples of Vis/NIR satellite missions are the advanced very high-resolution radiometer (AVHRR, [48]), the Landsat suites of satellite (e.g., [43]) and the moderate resolution imaging spectroradiometer (MODIS, [69]), and more recently, the visible infrared imaging radiometer suite (VIIRS, [134, 135]) and Sentinel-2 [58].

One major challenge in snow mapping using Vis/NIR is the discrimination between clouds and snow because of their similar behavior in the visible part of the spectrum (e.g., [71, 109]). If cloud coverage exceeds certain threshold percentages, a satellite scene can become useless for snow detection. Furthermore, snow grain size [55, 68, 132], impurities [5, 125, 146], and snow temperature influence the spectral behavior of different snow and ice surfaces in the Vis/NIR spectrum. Finally, snow cover extent does not provide a direct estimate of SWE. Indirect methods, such as retrospective (or reconstruction) techniques (e.g., [59, 81, 111, 112, 130, 133]) or data assimilation methods ("Remote Sensing of Seasonal Snow" section) must be used to estimate SWE.

Lidar Observations

Lidar is an active ranging system that provides high-resolution, high-accuracy surface elevation maps. The emitted laser pulse is reflected off multiple surface features back to the platform and the distance traveled is estimated and used to map surface height. Snow depth can be obtained from two co-registered lidar images—one each for snow-free and snow-covered dates—by differencing the snow surface and bare-ground elevations [36]. Airborne rather than spaceborne lidar systems [36, 126] are likely the most accurate to date, but are limited to targeted areas on the order of hundreds of kilometers and favorable weather conditions. Major limitations of lidar techniques are that (1) they observe snow depth and not SWE, thus assumptions or complementary in situ observations must be made about snow density [151]; and (2) they are available only at specific locations and for specific times, typically infrequently and often just once per season near peak SWE [106].

Passive Microwave Observations

The microwave radiation emitted by the Earth surface is attenuated by the snow mass on the ground. For this reason,

Table 1 Key visible and near-infrared (Vis/NIR) and passive microwave (PM) satellite missions that have been used for estimating seasonal snow

Satellite or sensor	Operational period	Spectral resolution	Spatial resolution	Spatial resolution	Spatial coverage
Landsat	1972–present	Vis/NIR	15–120 m	~ 16 days	Global
MODIS	2000–present	Vis/NIR	250–1000 m	< Daily	Global
AVHRR	1978–present	Vis/NIR	1090 m	Daily	Global
VIIRS	2011–present	Vis/NIR	375 m	< Daily	Global
Sentinel-2	2018–present	Vis/NIR	20 m	~ 5 days	Regional
SMMR	1978–1987	PM	25 km	Every other day	Global
SSM/I	1987–present	PM	25 km	Daily	Global
AMSR/E	2002–2011	PM	25 km	Daily	Global
AMSR 2	2012–present	PM	25 km	Daily	Global

microwave measurements are more sensitive to the mass of snow than Vis/NIR observations. Another advantage of passive microwave sensors with respect to the Vis/NIR is that they can detect snow at night and in the presence of clouds. Retrieval algorithms have been developed to estimate the snow depth from satellite-based microwave sensors. The retrievals are derived as a combination of microwave brightness temperature differences sensed at different frequencies, weighted by coefficients derived from the difference between vertical and horizontal polarizations. Examples of satellite-based missions that have been widely used to estimate SWE are listed in Table 1. These are the Scanning Multichannel Microwave Radiometer (SMMR, e.g., [23]), the Special Sensor Microwave/Image (SSM/I, e.g., [161]), and the Advanced Microwave Scanning Radiometer (AMSR-E and AMSR2, e.g., [84]).

There are a number of limitations to using passive microwave sensors to monitor seasonal snow. For example, the presence of liquid water in the snowpack [57, 84] and/or vegetation alters the radiation emitted by the surface [37]. Another major shortcoming is the spatial resolution of passive microwave measurements, which is on the order of tens of kilometers (i.e., much coarser than Vis/NIR). At these coarse scales, there can be significant sub-grid heterogeneity within a single remote sensing footprint, especially if estimating SWE in complex mountainous terrain. Finally, passive microwaves tend to saturate around 250 mm of SWE [56], and thus are of limited use to estimate deep snowpacks typical of Earth's mountain water towers [37, 166].

Active Microwave Observations

Active microwave sensors have the potential to determine snow depth or SWE from space with higher resolution than passive microwave sensors. Active microwave remote sensing measures the total backscattered power from snow-covered terrain. The total power received by the sensor can be expressed as the summation of backscatter from the air-snow boundary, the snow volume, and the snow-ground boundary attenuated by a factor depending on the layered snowpack properties and incidence angle [160]. Active microwave observations are not limited by weather or sun illumination conditions. While most active microwave studies have focused on the detection of snowmelt [118], some early studies showed a very limited sensitivity of active microwave sensors to snow mass [11, 85, 145, 152]. Recently, a few studies have demonstrated the possibility of using active microwave data to estimate SWE [95, 110]. Currently, Sentinel-1 or RADARSAT-2 is among the few Synthetic Aperture Radar (SAR) missions providing high-resolution backscatter measurements (at C-band; 5.4 GHz) with a revisit time of 6 days suitable for seasonal snow monitoring. Lievens et al. [98] demonstrated the value of including cross-polarized backscatter measurements from C-band SAR to retrieve snow depth in mountainous areas at regional scales. Furthermore, Conde et al. [29] used the SAR Interferometry technique and Sentinel-1 C-band data to retrieve SWE estimates with sub-centimeter measurement accuracy and a 20-m spatial resolution.

Gravimetric Observations

Less common ways to observe snow include gravity measurements. Gravity data collected by the Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-On (GRACE-FO) satellites can be used to estimate changes in the mass of terrestrial water storage caused by snow and other hydrological factors such as soil moisture, groundwater, lakes, and rivers [158]. However, the main shortcomings of GRACE estimates are related to the very coarse spatial resolution (~ 3 degrees) which limits application to larger river basins and continents, and to the fact that it observes the total sum of terrestrial water storage. Data assimilation of GRACE observations into land surface models [61–63] can spatially and vertically downscale the coarse resolution GRACE observations while characterizing finer-scale SWE estimates.

Snow Data Assimilation

Despite recent rapid advances, current remote sensing technology and techniques do not adequately meet global operational needs to map seasonal SWE. To this end, there is great promise in the combination of remote sensing technologies with modeling and data assimilation methods to produce optimal SWE maps with sufficient global coverage and near real-time estimates. In general terms, data assimilation is a transdisciplinary tool that has been used in fields spanning Earth sciences and extending to medicine [1] and socio-economics [76]. Figure 1 illustrates the data assimilation concept.

All estimates of a phenomenon or event (e.g., seasonal SWE) obtained either through modeling ("Snow Modeling" section) or observations ("Remote Sensing of Seasonal Snow" section) have inherent uncertainty and errors. Data assimilation is a tool to bridge models and observations in order to obtain optimized estimates of the specific phenomena of interest. Theoretically, the results of a data assimilation framework should be a statistically optimal estimate superior to that from either the model or observations alone. Modeling errors are linked to uncertainties due to parameterization schemes and input forcings ("Snow Modeling" section). Similarly, remote sensing observations are prone to observation errors due to measurement acquisition (e.g., sensor errors) and to representativeness of the observations. The latter encompasses errors due to unresolved scales and processes, observation-operator error, pre-processing or quality-control error, and

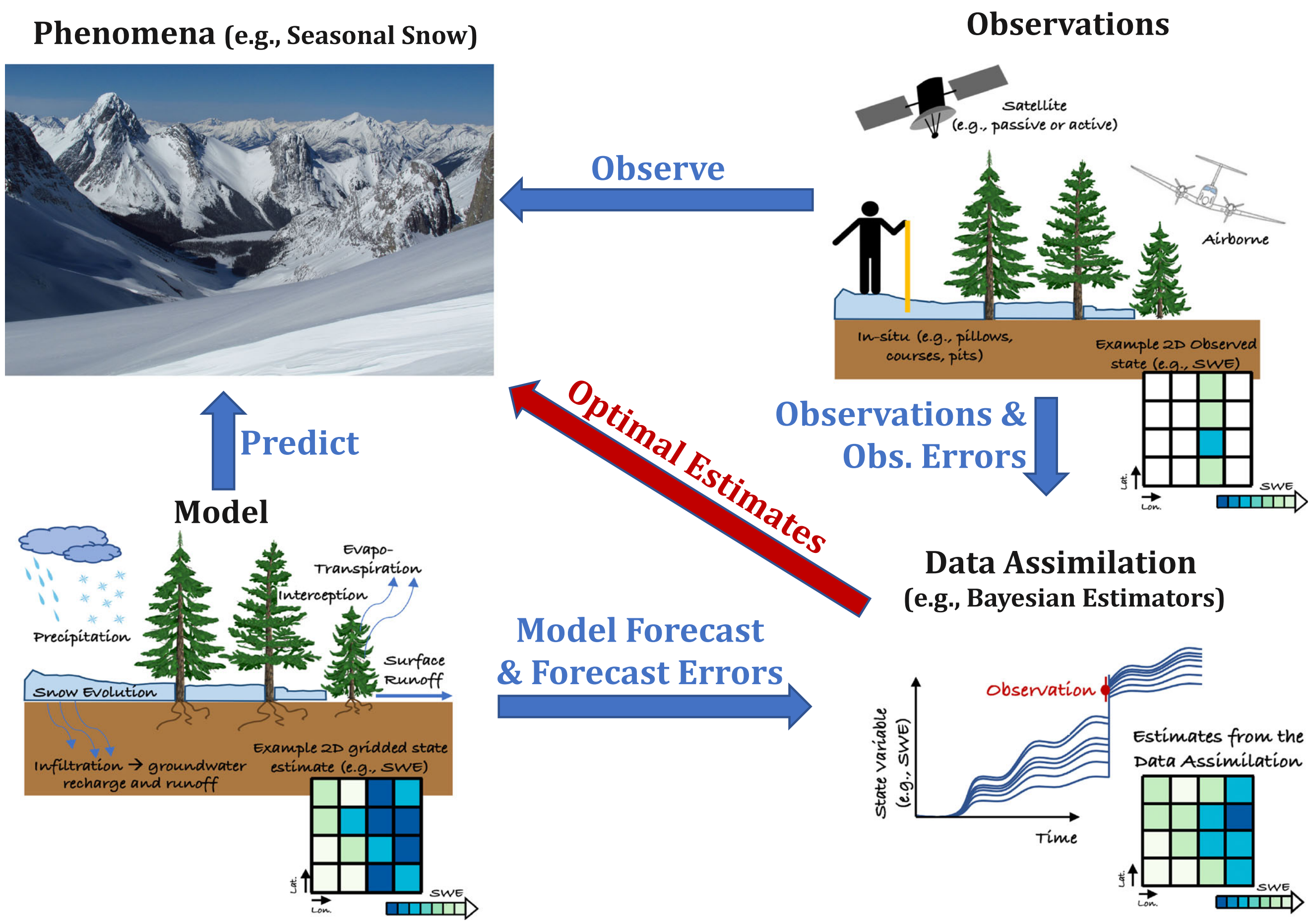

Fig. 1 Estimates of an environmental variable (e.g., seasonal snow) can be obtained from model predictions or from observations (remote sensing or in situ). Neither are perfect and they contain errors and uncertainties. Data assimilation can be seen as a method that combines the strengths of modeled and observed estimates to obtain an optimized set of estimates for the environmental variable

sampling error of the observation grid [80]. A remaining challenge is a better representation of errors in the observation and models used in data assimilation [90]. In general, modeling and observation errors are assumed to be Gaussian because of the relative simplicity and ease of implementation of statistical linear estimation under these conditions and because Gaussian probability distributions are fully determined by their mean and covariance [90], but the actual values of the errors and their full distributions are not known. Thus, statistical assumptions must be used. These assumptions range from which parameters, model inputs, or remote sensing observation to consider as uncertain, to the decision of the error magnitudes. Furthermore, modeling and observation errors are often assumed static in both time and space. In reality, errors vary in space and time and a fully space and time distributed error covariance should be considered [52].

Despite these remaining challenges, data assimilation has been used to improve modeled estimates of snow states, snow physics, model parameters, and sources of uncertainty [73]. There exists a wide variety of data assimilation techniques spanning degrees of complexity and the way in which modeling and observation errors are treated. They vary from the simple direct insertion of observations into the model (e.g., [97, 137]), where observations are treated as perfect (i.e., zero observation errors), to more mathematical Bayesian methods such as ensemble Kalman filter and particle filter approaches which are designed to account for the uncertainties of the model and observations using error statistics and an ensemble of possible model realizations. While modeling and observation errors are assumed to be of Gaussian shape in the ensemble Kalman filters, particle filters relax this assumption. The following sections expand on applications of data assimilation in the snow science community and cover studies across different spatial scales: from watershed to regional and global studies.

Direct Insertion

A simple direct insertion application is provided by Li et al. [97]. They directly insert a blended satellite- and model-based SWE product [105] for the initialization of a seasonal streamflow forecast model applied over the snow-dominated

Sierra Nevada. They demonstrate that a direct insertion of the blended SWE product improves the efficiency of the streamflow model predictions compared with the traditional approach where the model simulates seasonal SWE accumulation and melt using gridded meteorological data. In another example, Rodell and Houser [137] and Toure et al. [164] directly inserted MODIS snow cover extent in a global land surface model. They improved SWE model estimates using a rule that specifies whether to update the model with the measurements based on the difference between modeled and observed (from MODIS) snow cover extent. While important model improvements can be obtained with a direct insertion approach, the implicit assumption of the technique is that errors and uncertainties in the system are either acceptable or acceptably mitigated with rule-based insertion decisions.

Ensemble Kalman Filter

The data assimilation approach most commonly used by the snow science community is the Ensemble Kalman Filter (EnKF) in which error statistics are determined from an ensemble of possible model realizations. The literature is rich with articles that use EnKF techniques (and variations) to assimilate SWE observations (either from in situ or satellite remote sensing) or microwave radiance observations to directly adjust modeled SWE. Radiance assimilation is more effective because it overcomes difficulties arising from the non-unique and complex relationship linking the passive microwave signal to several snow properties (e.g., density, grain size/microstructure parameters, temperature, and wetness) [73]. This review reports only a few works on assimilating SWE or radiance observations. For example, [148] used an ensemble square-root Kalman filter (EnSRF, an approach similar to an EnKF) to assimilate in situ SWE data into a snow hydrologic model. They report improvements in the simulated SWE during both accumulation and melt periods. In the same year, Durand and Margulis [44] developed a point-scale radiometric data assimilation experiment where they used synthetic passive microwave observations and concluded that the EnKF was able to recover the true snowpack states. Similarly, Dechant and Moradkhani [35] examined the ability of an EnKF of remotely sensed microwave radiance data to improve SWE prediction and operational streamflow forecasts. Huang et al. [78] examined the potential of SWE data assimilation using the EnKF to improve seasonal streamflow predictions in the Pacific Northwest, the Rocky Mountains, and the Sierra Nevada. They found that most EnKF implementation variations resulted in improved streamflow prediction. To conclude, the scientific community agrees that EnKF assimilation of SWE or microwave radiance observations lead to overall improved estimates of seasonal snow and related variables (e.g., streamflow and snow cover).

The literature contains a few studies where the EnKF has been used to assimilate snow cover extent observations from a wide range of Vis/NIR satellite missions such as Landsat and/or MODIS. Su et al. [154] investigated the feasibility of an EnKF framework to assimilate satellite-observed snow cover extent over North America. The authors concluded that their framework accurately simulated the seasonal variability of SWE and reduced the uncertainties in the ensemble spread. Andreadis and Lettenmaier [4] and Clark et al. [24] used the EnKF to assimilate remotely sensed Vis/NIR snow cover observations into a hydrologic model. Their results showed that the EnKF is an effective and operationally feasible solution to update model predictions of snow cover extent. However, the EnKF performance is modest for estimating ephemeral SWE and limited for deeper snowpacks. As structured, the EnKF leverages the instantaneous correlation between modeled snow cover extent and SWE. This correlation tends to diminish for larger values of SWE, i.e., when changes in SWE do not correspond to changes in snow cover extent (i.e., snow cover extent saturates at 100%). To solve for this weak instantaneous correlation, Durand et al. [46], Girotto et al. [60], Margulis et al. [104], and Oaida et al. [122] presented a smoother version of the EnKF, the Ensemble Kalman Smoother (EnKS). In the EnKS, all snow cover extent observations within an assimilation window are assimilated; thus, multiple strengths of the observed snow cover extent signal are leveraged, not only the instantaneous acquisition.

The retrospective or reconstructive use of Vis/NIR satellite observations can provide accurate estimates of SWE. The general idea of such methods builds upon work on deterministic reconstruction techniques (e.g., [81, 111, 112, 133]) where the maximum (or peak) SWE can be retrieved from a retrospective accumulation of spring-summer potential melt energy fluxes coupled with the disappearance date of snow as ascertained from visible and near infrared images.

Particle Filter

Other, arguably more sophisticated methods include particle filter (PF) techniques [6]. Similar to the EnKF, the PF is a sequential Monte Carlo approach, but it does not depend on the assumption of a Gaussian distribution of errors. PF techniques typically require larger ensembles to characterize the full probability distribution of state variables and consequently their uncertainties via resampling sets of state variables. Leisenring and Moradkhani [93] assimilated SWE in the National Weather Service model while Margulis et al. [104] derived an ensemble PF approach to estimate SWE from the assimilation of snow cover extent. Both studies compared the PF with the EnKF. Their results suggest that the particle filter is superior to the EnKF-based methods for predicting model states and parameters. Thirel et al. [163] improved modeled snow cover extent and runoff by assimilating MODIS snow cover products into a distributed hydrological model using a PF. A similar approach used in Margulis et al. [106] assimilated infrequent (i.e., a couple of observations per year) lidar snow depth observations within a land surface model. They demonstrated that data assimilation provides a useful framework for leveraging infrequent remotely sensed snow depth observations to derive continuous (spatially and temporally) accurate estimates of unobserved variables such as SWE and snowmelt, even at times when observations are unavailable.

Spatially Distributed Updates

Spatial distribution updates are essential in operational analyses of in situ snow depth measurements. Most of the snow data assimilation research in the literature, however, are one-dimensional approaches, where one satellite observation type (i.e., SWE, snow depth, or snow cover extent) is used to update co-located modeled snow estimates. That is, snow updates can only be performed at the locations where an observation is available. One-dimensional techniques disregard spatial correlation across observations and model errors. In a few exceptions, De Lannoy et al. [32] and Cantet et al. [19] tested the effect of introducing spatial error correlation into snow data assimilation updates. De Lannoy et al. [32] assimilated coarse-scale (25 km) SWE observations into fine-scale (1 km) land model simulations and tested the effect of different spatial aggregation and correlation methods. Their results indicate that assimilating disaggregated fine-scale observations independently is less efficient than assimilating a collection of neighboring correlated coarser scale observations. Cantet et al. [19] assimilated SWE data from a sparse network of in situ snow observation stations using a PF. Their PF formulation included error spatial correlations to allow for snow states to be updated at locations where observations were not directly available. These few studies indicate that underlying spatial error correlations should be exploited to improve spatial estimates of seasonal snow.

Multi-sensor Data Assimilation

Only a few studies have focused on multi-spectral, multi-resolution, and multi-sensor data assimilation approaches. In fact, merging different observation types could be a challenging task [63]. A few exceptions include work by Durand and Margulis [45], De Lannoy et al. [33], Liu et al. [101], and Zhao and Yang [172]. Durand and Margulis [45] used EnKF in a multi-scale, multi-frequency radiometric data assimilation experiment using synthetic passive microwave radiance along with Vis/NIR snow cover extent observations. They stated that the combined assimilation of passive microwave and Vis/NIR observations resulted in overall improved snow predictive skill because of the positive synergy due to the complementary nature of the two observation types. Liu et al. [101] assimilated MODIS snow cover extent and AMSR-E snow depth products into the Noah land surface model and concluded that the assimilation of snow data consistently improved snow and streamflow predictions. De Lannoy et al. [33] assimilated AMSR-E SWE retrievals and MODIS snow cover extent observations. Their joint SWE and snow cover extent assimilation significantly improved root-mean-square error and correlation values. Zhao and Yang [172] assimilated MODIS, GRACE, and AMSR-E and found that the assimilation of MODIS snow cover fraction slightly improves snow estimation in mid and high latitudes while the assimilation of GRACE has potential in improving snow depth estimation in most high-latitude regions. The studies reviewed here agree that a broader range of assimilated observations is an essential for optimizing the information content provided to the models to produce the best possible estimates of seasonal snow.

Snow Data Assimilation in Operational Forecast Systems

Even if the research field in snow data assimilation has evolved significantly over the last decade, operational systems use methods that are much simpler than the state-of-the-art research [73]. For example, the GlobSnow product [103] provides global gridded information on snow extent and SWE across the Northern Hemisphere by incorporating in situ station snow depth observations, microwave emission modeling, and spaceborne passive microwave observations using an iterative least squares minimization scheme. Another widely used product is SNODAS, developed by the National Oceanic and Atmospheric Administration (NOAA) [8]. SNODAS incorporates in situ and airborne observations with model estimates to provide daily SWE at 1-km resolution across the continental USA [21]. Its assimilation procedure is a simple nudging technique that calculates differences between estimated and observed SWE values and then spatially interpolates these differences to the model grid. Furthermore, the Canadian Meteorological Center Daily Snow Depth Analysis product [15] uses a simple statistical interpolation method to blend observations with model estimates of snow [16]. Improved snow data assimilation schemes increase the skill of snow reanalysis products, which serve as an important baseline against which to assess climate model ensembles such as available in climate model intercomparison projects.

The work by Peings et al. [127] and Lin et al. [99] demonstrates that an accurate initialization of snow in a climate model has a positive impact on seasonal temperature forecast skill (Fig. 2). Lin et al. [99] showed that the assimilation of satellite measurements improves the initialization, with concomitant impacts on the forecast skill [88]. Improvements at low latitudes are seen immediately and last up to 60 days, whereas improvements at high latitudes appear later in transitional (fall and spring) seasons (Fig. 2). Finally, despite the importance of

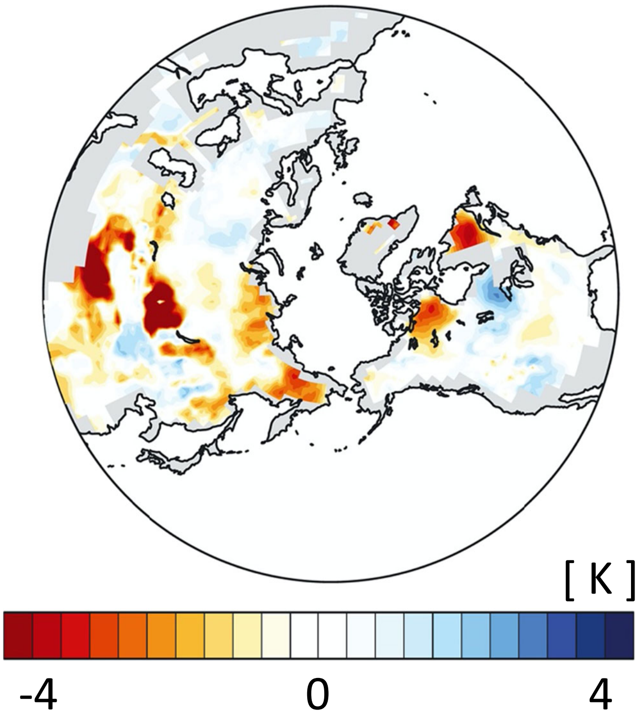

Fig. 2 Improvements in temperature 3-month prediction due to assimilation of MODIS snow cover extent. Improvements are expressed in terms of cumulative RMSE difference between the model run that assimilated snow information and a run with no assimilation. Negative values indicate reduced prediction errors and improved temperature predictions after using snow data assimilation–constrained land initializations. This is an edited version of Fig. 2 in Lin et al. [99]

snow in regulating weather and climate processes, only a few global weather forecast centers include snow data assimilation schemes in their forecasting systems. One example is the European Center for Medium Weather Forecast (ECMWF) center which assimilates in situ snow depth and satellite-derived snow cover extent [34].

Zsoter et al. [173] address an ongoing challenge in Earth system modeling and data assimilation applications. They show that while data assimilation of snow properties is a critical component of numerical weather prediction, the addition or removal of water neither conserves water mass nor does it reliably improve hydrologic prediction. The authors attribute the issue to getting the right answers for the wrong reasons; improvements in one model variable expose other model deficiencies. They call for a need to consider the whole Earth system in data assimilation and model coupling efforts. Such holistic Earth system approaches and the inclusion of diverse observations promise to provide robust information to improve our ability to map, model, and project with a better degree of accuracy past, current, and future seasonal snow characteristics and the effects of snow on the entire Earth system.

Conclusions

The international Earth sciences community lacks an accurate way to estimate seasonal snow changes at sufficiently high temporal and spatial resolutions and with global coverage using any single in situ, remote sensing or modeling technique. In this paper, we review current modeling, remote sensing, and assimilation techniques used to estimate seasonal snow and elucidate the remaining challenges associated with each system.

The representation of snow in hydrologic and Earth system models has steadily improved over the last 60 years. To date, modeling efforts have provided the most spatially and temporally complete estimates of local, regional, and global snow properties; however, the accuracy of snow model estimates remains hindered by uncertain forcing and parameters, and error-prone model structures and process representations.

Satellite and airborne remote sensing allow for extensive and global coverage of seasonal snow even in remote, complex mountainous regions. While snow cover extent and related surface properties are generally obtained reliably with high spatial and temporal resolution from visible and near infrared data, we critically lack similar robust estimates of snow mass relevant to water resource applications [26]. Compared with Vis/NIR data, microwave measurements are more directly related to the mass of snow. While active microwave data have recently been found suitable for providing temporal and spatial resolutions for seasonal snow monitoring, passive microwave techniques are not useful for estimating deep or wet snow at an acceptable spatial resolution capable of resolving global snow processes inclusive of Earth's mountain water towers. Airborne lidar systems are, to date, the most accurate methods to retrieve seasonal snow, but they only observe snow depth (not SWE) and are limited to targeted regions and for specific, infrequent times.

Data assimilation is a viable way to converge different temporal and spatial resolutions of in situ and remotely sensed observations and as a useful technology to bridge the scale gap between these observations and models. In fact, the assimilation of satellite and airborne observations leads, in general, to overall improved estimates of seasonal snow and related variables. Some remaining challenges in the snow data assimilation field include research in the effects of underlying spatial error correlations in data assimilation to improve the spatial estimates of SWE, and possibly merging multiple observations to improve snow model accuracy. Finally, even if the research field in snow data assimilation has evolved significantly, operational and weather forecasting systems use methods (if any) that are much simpler than the state of the art. The inclusion of a broader range of observations is an active and emergent research field as multi-sensor, multi-resolution snow observations become available.

These data assimilation efforts promise to provide robust and diverse information to improve our ability to map, model, and project past, current, and future characteristics and the effects of seasonal snow on the Earth system.

References

1. Albers DJ, Levine M, Gluckman B, Ginsberg H, Hripcsak G, Mamykina L. Personalized glucose forecasting for type 2 diabetes using data assimilation. PLoS Comput Biol. 2017;13(4): e1005232.
2. Allchin MI, Déry SJ. A spatio-temporal analysis of trends in northern hemisphere snow-dominated area and duration, 1971–2014. Ann Glaciol. 2017;58(75pt1):21–35.
3. Anderson MG, Burt TP, editors. Hydrological forecasting, vol. 372. Chichester: Wiley; 1985.
4. Andreadis KM, Lettenmaier DP. Assimilating remotely sensed snow observations into a macroscale hydrology model. Adv Water Resour. 2006;29(6):872–86.
5. Aoki T, Motoyoshi H, Kodama Y, Yasunari TJ, Sugiura K. Variations of the snow physical parameters and their effects on albedo in Sapporo, Japan. Ann Glaciol. 2007;46:375–81.
6. Arulampalam MS, Maskell S, Gordon N, Clapp T. A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. IEEE Trans Signal Process. 2002;50(2):174–88.
7. Barnett TP, Adam JC, Lettenmaier DP. Potential impacts of a warming climate on water availability in snow-dominated regions. Nature. 2005;438(7066):303–9.
8. Barrett AP. National operational hydrologic remote sensing center snow data assimilation system (SNODAS) products at NSIDC. Boulder, CO: National Snow and Ice Data Center, Cooperative Institute for Research in Environmental Sciences; 2003. p. 19.
9. Bavay M, Lehning M, Jonas T, Löwe H. Simulations of future snow cover and discharge in Alpine headwater catchments. Hydrol Process Int J. 2009;23(1):95–108.
10. Berghuijs WR, Woods RA, Hutton CJ, Sivapalan M. Dominant flood generating mechanisms across the United States. Geophys Res Lett. 2016;43(9):4382–90.
11. Bernier M, Fortin JP, Gauthier Y, Gauthier R, Roy R, Vincent P. Determination of snow water equivalent using RADARSAT SAR data in eastern Canada. Hydrol Process. 1999;13(18):3041–51.
12. Bonan GB. The land surface climatology of the NCAR Land Surface Model coupled to the NCAR Community Climate Model. J Clim. 1998;11(6):1307–26.
13. Bormann KJ, Brown RD, Derksen C, Painter TH. Estimating snow-cover trends from space. Nat Clim Chang. 2018;8(11): 924–8.
14. Brown and Derksen. Is Eurasian October snow cover extent increasing? Environ Res Lett. 2013. https://doi.org/10.1088/1748-9326/8/2/024006.
15. Brown RD, Brasnett B. Updated annually. Canadian Meteorological Centre (CMC) daily snow depth analysis data, version 1. Boulder, Colorado USA: NASA National Snow and Ice Data Center Distributed Active Archive Center; 2010.
16. Brown RD, Brasnett B, Robinson D. Gridded North American monthly snow depth and snow water equivalent for GCM evaluation. Atmosphere-Ocean. 2003;41(1):1–14.
17. Brown, et al. Arctic terrestrial snow cover. In: Snow, Water, Ice and Permafrost in the Arctic (SWIPA). Oslo, Norway: Arctic Monitoring and Assessment Programme (AMAP); 2017. p. 25–64.
18. Brun E, David P, Sudul M, Brunot G. A numerical model to simulate snow-cover stratigraphy for operational avalanche forecasting. J Glaciol. 1992;38(128):13–22.
19. Cantet P, Boucher MA, Lachance-Coutier S, Turcotte R, Fortin V. Using a particle filter to estimate the spatial distribution of the snowpack water equivalent. J Hydrometeorol. 2019;20(4):577–94.
20. Carroll TR. Operational airborne measurements of snow water equivalent and soil moisture using terrestrial gamma radiation in the United States. In: Goodison B, Barry RG, Dozier J, editors. Large scale effects of seasonal snow cover (Proceedings of the Vancouver Symposium, August 1987). Vancouver, BC: IAHS; 1987. p. 213–23.
21. Carroll T. Airborne gamma radiation snow survey program: a user's guide, version 5.0. In: National Operational Hydrologic Remote Sensing Center (NOHRSC), Chanhassen; 2001. p. 14.
22. Carroll SS, Carroll TR. Effect of uneven snow cover on airborne snow water equivalent estimates obtained by measuring terrestrial gamma radiation. Water Resour Res. 1989;25(7):1505–10.
23. Chang ATC, Foster JL, Hall DK. Nimbus-7 SMMR derived global snow cover parameters. Ann Glaciol. 1987;9:39–44.
24. Clark MP, Slater AG, Barrett AP, Hay LE, McCabe GJ, Rajagopalan B, et al. Assimilation of snow covered area information into hydrologic and land-surface models. Adv Water Resour. 2006;29(8):1209–21.
25. Clark MP, Bierkens MF, Samaniego L, Woods RA, Uijlenhoet R, Bennett KE, et al. The evolution of process-based hydrologic models: historical challenges and the collective quest for physical realism. Hydrology and Earth System Sciences (online). 2017;21(LA-UR-17-27603).
26. Clifford D. Global estimates of snow water equivalent from passive microwave instruments: history, challenges and future developments. Int J Remote Sens. 2010;31(14):3707–26.
27. Cline DW, Bales RC, Dozier J. Estimating the spatial distribution of snow in mountain basins using remote sensing and energy balance modeling. Water Resour Res. 1998;34(5):1275–85.
28. Cohen J, Entekhabi D. The influence of snow cover on northern hemisphere climate variability. Atmosphere-Ocean. 2001;39(1): 35–53.
29. Conde V, Nico G, Mateus P, Catalão J, Kontu A, Gritsevich M. On the estimation of temporal changes of snow water equivalent by spaceborne SAR interferometry: a new application for the Sentinel-1 mission. J Hydrol Hydromech. 2019;67(1):93–100.
30. Cortés G, Girotto M, Margulis SA. Analysis of sub-pixel snow and ice extent over the extratropical Andes using spectral unmixing of historical Landsat imagery. Remote Sens Environ. 2014;141:64–78.
31. Croce P, Formichi P, Landi F, Mercogliano P, Bucchignani E, Dosio A, et al. The snow load in Europe and the climate change. Clim Risk Manag. 2018;20:138–54.
32. De Lannoy GJ, Reichle RH, Houser PR, Arsenault KR, Verhoest NE, Pauwels VR. Satellite-scale snow water equivalent assimilation into a high-resolution land surface model. J Hydrometeorol. 2010;11(2):352–69.
33. De Lannoy GJ, Reichle RH, Arsenault KR, Houser PR, Kumar S, Verhoest NE, et al. Multiscale assimilation of advanced microwave scanning radiometer–EOS snow water equivalent and moderate resolution imaging Spectroradiometer snow cover fraction observations in northern Colorado. Water Resour Res. 2012;48(1).
34. de Rosnay P, Balsamo G, Albergel C, Munoz-Sabater J, Isaksen L. Initialisation of land surface variables for numerical weather *prediction*. Surv Geophys. 2014;35:607–21.
35. Dechant C, Moradkhani H. Radiance data assimilation for operational snow and streamflow forecasting. Adv Water Resour. 2011;34(3):351–64.

36. Deems JS, Painter TH, Finnegan DH. LiDAR measurements of snow depth: a review. J Glaciol. 2013;59(215):467–79.
37. Derksen C. The contribution of AMSR-E 18.7 and 10.7 GHz measurements to improved boreal forest snow water equivalent retrievals. Remote Sens Environ. 2008;112(5):2701–10.
38. Déry SJ, Brown RD. Recent Northern Hemisphere snow cover extent trends and implications for the snow-albedo feedback. Geophys Res Lett. 2007;34(22).
39. Descamps S, Aars J, Fuglei E, Kovacs KM, Lydersen C, Pavlova O, et al. Climate change impacts on wildlife in a high Arctic archipelago–Svalbard, Norway. Glob Chang Biol. 2017;23(2): 490–502.
40. Dietz AJ, Kuenzer C, Gessner U, Dech S. Remote sensing of snow–a review of available methods. Int J Remote Sens. 2012;33(13):4094–134.
41. Dirmeyer PA, Gao X, Zhao M, Guo Z, Oki T, Hanasaki N. GSWP-2: multimodel analysis and implications for our perception of the land surface. Bull Am Meteorol Soc. 2006;87(10):1381–98.
42. Domine F, Salvatori R, Legagneux L, Salzano R, Fily M, Casacchia R. Correlation between the specific surface area and the short wave infrared (SWIR) reflectance of snow. Cold Reg Sci Technol. 2006;46(1):60–8.
43. Dozier J. Spectral signature of alpine snow cover from the Landsat thematic mapper. Remote Sens Environ. 1989;28:9–22.
44. Durand M, Margulis SA. Feasibility test of multifrequency radiometric data assimilation to estimate snow water equivalent. J Hydrometeorol. 2006;7(3):443–57.
45. Durand M, Margulis SA. Correcting first-order errors in snow water equivalent estimates using a multifrequency, multiscale radiometric data assimilation scheme. J Geophys Res-Atmos. 2007;112(D13).
46. Durand M, Molotch NP, Margulis SA. A Bayesian approach to snow water equivalent reconstruction. J Geophys Res-Atmos. 2008;113(D20).
47. Dutra E, Schär C, Viterbo P, Miranda PM. Land-atmosphere coupling associated with snow cover. Geophys Res Lett. 2011;38(15).
48. Emery C, Fowler T, Haran J, Key J, Maslanik TS. AVHRR polar pathfinder twice-daily 5 km EASE-grid composites, version 3. Boulder, Colorado USA. NSIDC: National Snow and Ice Data Center; 2000.
49. Essery R, Etchevers P. Parameter sensitivity in simulations of snowmelt. J Geophys Res-Atmos. 2004;109(D20).
50. Essery R, Martin E, Douville H, Fernandez A, Brun E. A comparison of four snow models using observations from an alpine site. Clim Dyn. 1999;15(8):583–93.
51. Essery R, Rutter N, Pomeroy J, Baxter R, Stähli M, Gustafsson D, et al. SNOWMIP2: an evaluation of forest snow process simulations. Bull Am Meteorol Soc. 2009;90(8):1120–36.
52. Evensen G. Data assimilation: the ensemble Kalman filter: Springer Science & Business Media; 2009.
53. Foster JL, Hall DK, Chang ATC, Rango A. An overview of passive microwave snow research and results. Rev Geophys. 1984;22(2):195–208.
54. Foster J, Liston G, Koster R, Essery R, Behr H, Dumenil L, et al. Snow cover and snow mass intercomparisons of general circulation models and remotely sensed datasets. J Clim. 1996;9(2):409–26.
55. Foster JL, Hall DK, Chang AT, Rango A, Wergin W, Erbe E. Effects of snow crystal shape on the scattering of passive microwave radiation. IEEE Trans Geosci Remote Sens. 1999;37(2): 1165–8.
56. Foster JL, Sun C, Walker JP, Kelly R, Chang A, Dong J, et al. Quantifying the uncertainty in passive microwave snow water equivalent observations. Remote Sens Environ. 2005;94(2):187–203.
57. Frei A, Tedesco M, Lee S, Foster J, Hall DK, Kelly R, et al. A review of global satellite-derived snow products. Adv Space Res. 2012;50(8):1007–29.
58. Gascoin S, Grizonnet M, Bouchet M, Salgues G, Hagolle O. Theia snow collection: high-resolution operational snow cover maps from Sentinel-2 and Landsat-8 data. Earth Syst Sci Data. 2019;11(2):493–514.
59. Girotto M, Margulis SA, Durand M. Probabilistic SWE reanalysis as a generalization of deterministic SWE reconstruction techniques. Hydrol Process. 2014a;28(12):3875–95.
60. Girotto M, Cortés G, Margulis SA, Durand M. Examining spatial and temporal variability in snow water equivalent using a 27 year reanalysis: K ern R iver watershed, Sierra Nevada. Water Resour Res. 2014b;50(8):6713–34.
61. Girotto M, De Lannoy GJ, Reichle RH, Rodell M. Assimilation of gridded terrestrial water storage observations from GRACE into a land surface model. Water Resour Res. 2016;52(5):4164–83.
62. Girotto M, De Lannoy GJ, Reichle RH, Rodell M, Draper C, Bhanja SN, et al. Benefits and pitfalls of GRACE data assimilation: a case study of terrestrial water storage depletion in India. Geophys Res Lett. 2017;44(9):4107–15.
63. Girotto M, Reichle RH, Rodell M, Liu Q, Mahanama S, De Lannoy GJ. Multi-sensor assimilation of SMOS brightness temperature and GRACE terrestrial water storage observations for soil moisture and shallow groundwater estimation. Remote Sens Environ. 2019;227:12–27.
64. Golding DL, Swanson RH. Snow accumulation and melt in small forest openings in Alberta. Can J For Res. 1978;8(4):380–8.
65. Gong G, Entekhabi D, Cohen J, Robinson D. Sensitivity of atmospheric response to modeled snow anomaly characteristics. J Geophys Res-Atmos. 2004;109(D6).
66. Groffman PM, Driscoll CT, Fahey TJ, Hardy JP, Fitzhugh RD, Tierney GL. Colder soils in a warmer world: a snow manipulation study in a northern hardwood forest ecosystem. Biogeochemistry. 2001;56(2):135–50.
67. Hagopian J, Bolcar M, Chambers J, Crane A, Eegholm B, Evans T, et al. Advanced topographic laser altimeter system (ATLAS) receiver telescope assembly (RTA) and transmitter alignment and test. In: Earth Observing Systems XXI (Vol. 9972, p. 997207). International Society for Optics and Photonics; 2016, September.
68. Hall DK, Martinec J. Remote sensing of snow and ice. Principles and Applications of Imaging Radar. 1985:677–703.
69. Hall DK, Riggs GA, Salomonson VV, DiGirolamo NE, Bayr KJ. MODIS snow-cover products. Remote Sens Environ. 2002;83(1–2):181–94.
70. Hall DK, Box JE, Casey KA, Hook SJ, Shuman CA, Steffen K. Comparison of satellite-derived and in-situ observations of ice and snow surface temperatures over Greenland. Remote Sens Environ. 2008;112(10):3739–49.
71. Hall DK, Riggs GA, DiGirolamo NE, Román MO. MODIS cloud-gap filled snow-cover products: advantages and uncertainties. Hydrol Earth Syst Sci Discuss. 2019:1–23.
72. Hammond JC, Saavedra FA, Kampf SK. Global snow zone maps and trends in snow persistence 2001–2016. Int J Climatol. 2018;38(12):4369–83.
73. Helmert J, Şensoy Şorman A, Alvarado Montero R, De Michele C, de Rosnay P, Dumont M, et al. Review of snow data assimilation methods for hydrological, land surface, meteorological and climate models: results from a COST HarmoSnow survey. Geosciences. 2018;8(12):489.
74. Henderson GR, Peings Y, Furtado JC, Kushner PJ. Snow–atmosphere coupling in the northern hemisphere. Nat Clim Chang. 2018;1.
75. Hori, et al. A 38-year (1978–2015) northern hemisphere daily now cover extent product derived using consistent objective criteria

from satellite-borne optical sensors. Remote Sens Environ. 2017. https://doi.org/10.1016/j.rse.2017.01.023.
76. Houser PR. Improved disaster management using data assimilation. In: Approaches to disaster management-examining the implications of hazards, Emergencies and Disasters: IntechOpen; 2013.
77. Houser PR, Shuttleworth WJ, Famiglietti JS, Gupta HV, Syed KH, Goodrich DC. Integration of soil moisture remote sensing and hydrologic modeling using data assimilation. Water Resour Res. 1998;34(12):3405–20.
78. Huang C, Newman AJ, Clark MP, Wood AW, Zheng X. Evaluation of snow data assimilation using the ensemble Kalman filter for seasonal streamflow prediction in the western United States. Hydrol Earth Syst Sci. 2017;21(1):635–50.
79. Huntington TG. Evidence for intensification of the global water cycle: review and synthesis. J Hydrol. 2006;319(1–4):83–95.
80. Janjić T, Bormann N, Bocquet M, Carton JA, Cohn SE, Dance SL, et al. On the representation error in data assimilation. Q J R Meteorol Soc. 2018;144(713):1257–78.
81. Jepsen SM, Molotch NP, Williams MW, Rittger KE, Sickman JO. Interannual variability of snowmelt in the Sierra Nevada and Rocky Mountains, United States: examples from two alpine watersheds. Water Resour Res. 2012;48(2).
82. Jordan, R. (1991). A one-dimensional temperature model for a snow cover: technical documentation for SNTHERM. 89 (No. CRREL-SR-91-16). Cold regions research and engineering lab Hanover NH.
83. Jost G, Weiler M, Gluns DR, Alila Y. The influence of forest and topography on snow accumulation and melt at the watershed-scale. J Hydrol. 2007;347(1–2):101–15.
84. Kelly R. The AMSR-E snow depth algorithm: description and initial results. J Remote Sens Soc Jpn. 2009;29(1):307–17.
85. Kendra JR, Sarabandi K, Ulaby FT. Radar measurements of snow: experiment and analysis. IEEE Trans Geosci Remote Sens. 1998;36(3):864–79.
86. Kim, E. J., Gatebe, C. K., Hall, D. K., & Kang, D. H. (2018). NASA's SnowEx campaign and measuring global snow from space (GSFC-E-DAA-TN55784).
87. Klein G, Vitasse Y, Rixen C, Marty C, Rebetez M. Shorter snow cover duration since 1970 in the Swiss Alps due to earlier snowmelt more than to later snow onset. Clim Chang. 2016;139(3–4):637–49.
88. Koster RD, Betts AK, Dirmeyer PA, Bierkens M, Bennett KE, Déry SJ, et al. Hydroclimatic variability and predictability: a survey of recent research. Hydrol Earth Syst Sci. 2017;21(7):3777–98.
89. Krinner G, Derksen C, Essery R, Flanner M, Hagemann S, Clark M, et al. ESM-SnowMIP: assessing snow models and quantifying snow-related climate feedbacks. Geosci Model Dev. 2018;11:5027–49.
90. Lahoz WA, Schneider P. Data assimilation: making sense of earth observation. Front Environ Sci. 2014;2:16.
91. Lawrence DM, Slater AG, Tomas RA, Holland MM, Deser C. Accelerated Arctic land warming and permafrost degradation during rapid sea ice loss. Geophys Res Lett. 2008;35(11).
92. Lehning M, Bartelt P, Brown B, Russi T, Stöckli U, Zimmerli M. SNOWPACK model calculations for avalanche warning based upon a new network of weather and snow stations. Cold Reg Sci Technol. 1999;30(1–3):145–57.
93. Leisenring M, Moradkhani H. Snow water equivalent prediction using Bayesian data assimilation methods. Stoch Env Res Risk A. 2011;25(2):253–70.
94. Lemmetyinen J, Pulliainen J, Arslan A, Kontu A, Rautiainen K, Vehviläinen J, et al. Analysis of active and passive microwave observations from the NoSREx campaign. In: 2011 IEEE International Geoscience and Remote Sensing Symposium: IEEE; 2011. p. 2737–40.
95. Lemmetyinen J, Derksen C, Rott H, Macelloni G, King J, Schneebeli M, et al. Retrieval of effective correlation length and snow water equivalent from radar and passive microwave measurements. Remote Sens. 2018;10(2):170.
96. Li D, Durand M, Margulis SA. Potential for hydrologic characterization of deep mountain snowpack via passive microwave remote sensing in the Kern River basin, Sierra Nevada, USA. Remote Sens Environ. 2012;125:34–48.
97. Li D, Lettenmaier DP, Margulis SA, Andreadis K. The value of accurate high-resolution and spatially continuous snow information to streamflow forecasts. J Hydrometeorol. 2019;20(4):731–49.
98. Lievens H, Demuzere M, Marshall HP, Reichle RH, Brucker L, Brangers I, et al. Snow depth variability in the Northern Hemisphere mountains observed from space. Nat Commun. 2019;10(1):1–12.
99. Lin P, Wei J, Yang ZL, Zhang Y, Zhang K. Snow data assimilation-constrained land initialization improves seasonal temperature prediction. Geophys Res Lett. 2016;43(21):11–423.
100. Liu Y, Margulis S. Deriving Bias and uncertainty in MERRA-2 snowfall precipitation over High Mountain Asia. Front Earth Sci. 2019;7:280.
101. Liu Y, Peters-Lidard CD, Kumar S, Foster JL, Shaw M, Tian Y, et al. Assimilating satellite-based snow depth and snow cover products for improving snow predictions in Alaska. Adv Water Resour. 2013;54:208–27.
102. Lundquist J, Hughes M, Gutmann E, Kapnick S. Our skill in modeling mountain rain and snow is bypassing the skill of our observational networks. Bull Am Meteorol Soc. 2019;2019.
103. Luojus, K., Pullianinen, J., Takala, M., Lemmetyinen, J., Kangwa, M., Smolander, T., ... & Pinnock, S. (2013). ESA Globsnow: Algorithm Theoretical Basis Document-SWE-algorithm.
104. Margulis SA, Girotto M, Cortés G, Durand M. A particle batch smoother approach to snow water equivalent estimation. J Hydrometeorol. 2015;16(4):1752–72.
105. Margulis SA, Cortés G, Girotto M, Durand M. A Landsat-era Sierra Nevada snow reanalysis (1985–2015). J Hydrometeorol. 2016;17(4):1203–21.
106. Margulis SA, Fang Y, Li D, Lettenmaier DP, Andreadis K. The utility of infrequent snow depth images for deriving continuous space-time estimates of seasonal snow water equivalent. Geophys Res Lett. 2019;46(10):5331–40.
107. Mätzler C, Wiesmann A. Extension of the microwave emission model of layered snowpacks to coarse-grained snow. Remote Sens Environ. 1999;70(3):317–25.
108. Meiman J, Froehlich H, Dils RE. 1968. Snow accumulation in relation to elevation and forest canopy. Paper Presented at National Fall Meeting. American Geophysical Union: San Francisco; 8.
109. Miller SD, Lee TF, Fennimore RL. Satellite-based imagery techniques for daytime cloud/snow delineation from MODIS. J Appl Meteorol. 2005;44(7):987–97.
110. Moller D, Andreadis KM, Bormann KJ, Hensley S, Painter TH. Mapping snow depth from Ka-band interferometry: proof of concept and comparison with scanning lidar retrievals. IEEE Geosci Remote Sens Lett. 2017;14(6):886–90.
111. Molotch NP, Margulis SA. Estimating the distribution of snowwater equivalent using remotely sensed snow cover data and a spatially distributed snowmelt model: a multi-resolution, multisensor comparison. Adv Water Resour. 2008;31:1503–14.
112. Molotch NP, Painter TH, Bales RC, Dozier J. Incorporating remotely-sensed snow albedo into a spatially-distributed snowmelt model. Geophys Res Lett. 2004;31(3).

113. Mote PW, Li S, Lettenmaier DP, Xiao M, Engel R. Dramatic declines in snowpack in the western US. Npj Climate Atmos Sc. 2018;1(1):2.
114. Musselman KN, Pomeroy JW, Essery RL, Leroux N. Impact of windflow calculations on simulations of alpine snow accumulation, redistribution and ablation. Hydrol Process. 2015;29(18): 3983–99.
115. Musselman KN, Clark MP, Liu C, Ikeda K, Rasmussen R. Slower snowmelt in a warmer world. Nat Clim Chang. 2017;7(3):214–9.
116. Musselman KN, Lehner F, Ikeda K, Clark MP, Prein AF, Liu C, et al. Projected increases and shifts in rain-on-snow flood risk over western North America. Nat Clim Chang. 2018;8(9):808.
117. Nadim F, Kjekstad O, Peduzzi P, Herold C, Jaedicke C. Global landslide and avalanche hotspots. Landslides. 2006;3(2):159–73.
118. Nagler T, Rott H, Ripper E, Bippus G, Hetzenecker M. Advancements for snowmelt monitoring by means of sentinel-1 SAR. Remote Sens. 2016;8(4):348.
119. Navari M, Margulis SA, Tedesco M, Fettweis X, Alexander PM. Improving Greenland surface mass balance estimates through the assimilation of MODIS albedo: a case study along the K-transect. Geophys Res Lett. 2018;45(13):6549–56.
120. Niu GY, Yang ZL, Mitchell KE, Chen F, Ek MB, Barlage M, et al. The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. J Geophys Res-Atmos. 2011;116(D12).
121. Notarnicola C. Hotspots of snow cover changes in global mountain regions over 2000–2018. Remote Sens Environ. 2020;243: 111781.
122. Oaida CM, Reager JT, Andreadis KM, David CH, Levoe SR, Painter TH, et al. A high-resolution data assimilation framework for snow water equivalent estimation across the Western United States and validation with the airborne snow observatory. J Hydrometeorol. 2019;20(3):357–78.
123. Ohmura A. Physical basis for the temperature-based melt-index method. J Appl Meteorol. 2001;40(4):753–61.
124. Painter TH, Rittger K, McKenzie C, Slaughter P, Davis RE, Dozier J. Retrieval of subpixel snow covered area, grain size, and albedo from MODIS. Remote Sens Environ. 2009;113(4): 868–79.
125. Painter TH, Bryant AC, Skiles SM. Radiative forcing by light absorbing impurities in snow from MODIS surface reflectance data. Geophys Res Lett. 2012;39(17).
126. Painter TH, Berisford DF, Boardman JW, Bormann KJ, Deems JS, Gehrke F, et al. The airborne snow observatory: fusion of scanning lidar, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo. Remote Sens Environ. 2016;184:139–52.
127. Peings Y, Douville H, Alkama R, Decharme B. Snow contribution to springtime atmospheric predictability over the second half of the twentieth century. Clim Dyn. 2011;37(5–6):985–1004.
128. Peters-Lidard CD, Hossain F, Leung LR, McDowell N, Rodell M, Tapiador FJ, et al. 100 years of progress in hydrology. Meteorol Monogr. 2019;59:25–1.
129. Pierce DW, Barnett TP, Hidalgo HG, Das T, Bonfils C, Santer BD, et al. Attribution of declining western US snowpack to human effects. J Clim. 2008;21(23):6425–44.
130. Raleigh MS, Lundquist JD. Comparing and combining SWE estimates from the SNOW-17 model using PRISM and SWE reconstruction. Water Resour Res. 2012;48(1).
131. Raleigh MS, Livneh B, Lapo K, Lundquist JD. How does availability of meteorological forcing data impact physically based snowpack simulations? J Hydrometeorol. 2016;17(1):99–120.
132. Rango A. Spaceborne remote sensing for snow hydrology applications. Hydrol Sci J. 1996;41(4):477–94.
133. Rice R, Bales RC, Painter TH, Dozier J. Snow water equivalent along elevation gradients in the Merced and Tuolumne River basins of the Sierra Nevada. Water Resour Res. 2011;47(8).
134. Riggs, G. A., Hall, D. K., and Román, M. O.: MODIS snow products user guide for collection 6 (C6), available at: http://modis-snow-ice.gsfc.nasa.gov/?c=userguides, 2016a.
135. Riggs, G. A., Hall, D. K., and Román, M. O.: VIIRS snow products user guide for collection 1 (C1), available at: http://modis-snow-ice.gsfc.nasa.gov/?c=userguides, 2016b.
136. Riggs GA, Hall DK, Román MO. Overview of NASA's MODIS and visible infrared imaging radiometer suite (VIIRS) snow-cover earth system data records. Earth Syst Sci Data. 2017;9(2):765–77.
137. Rodell M, Houser PR. Updating a land surface model with MODIS-derived snow cover. J Hydrometeorol. 2004;5(6):1064–75.
138. Rooney JF Jr. The urban snow hazard in the United States: an appraisal of disruption. Geogr Rev. 1967:538–59.
139. Rosenthal W, Dozier J. Automated mapping of montane snow cover at subpixel resolution from the Landsat Thematic Mapper. Water Resour Res. 1996;32(1):115–30.
140. Rupp DE, Mote PW, Bindoff NL, Stott PA, Robinson DA. Detection and attribution of observed changes in northern hemisphere spring snow cover. J Clim. 2013;26(18):6904–14.
141. Schlosser CA, Robock A, Vinnikov KY, Speranskaya NA, Xue Y. 18-year land-surface hydrology model simulations for a midlatitude grassland catchment in Valdai, Russia. Mon Weather Rev. 1997;125(12):3279–96.
142. Schmidt RA. Properties of blowing snow. Rev Geophys. 1982;20(1):39–44.
143. Schmugge TJ, Kustas WP, Ritchie JC, Jackson TJ, Rango A. Remote sensing in hydrology. Adv Water Resour. 2002;25(8): 1367–85.
144. Senan R, Orsolini YJ, Weisheimer A, Vitart F, Balsamo G, Stockdale TN, et al. Impact of springtime Himalayan–Tibetan Plateau snowpack on the onset of the Indian summer monsoon in coupled seasonal forecasts. Clim Dyn. 2016;47(9):2709–25.
145. Shi J, Dozier J. Estimation of snow water equivalence using SIR-C/X-SAR. I Inferring snow density and subsurface properties. IEEE Transactions on Geoscience and Remote Sensing. 2000;38(6):2465–74.
146. Skiles SM, Painter TH. Toward understanding direct absorption and grain size feedbacks by dust radiative forcing in snow with coupled snow physical and radiative transfer modeling. Water Resour Res. 2019;55:7362–78.
147. Skiles SM, Flanner M, Cook JM, Dumont M, Painter TH. Radiative forcing by light-absorbing particles in snow. Nat Clim Chang. 2018;8(11):964–71.
148. Slater AG, Clark MP. Snow data assimilation via an ensemble Kalman filter. J Hydrometeorol. 2006;7(3):478–93.
149. Slater AG, Schlosser CA, Desborough CE, Pitman AJ, Henderson-Sellers A, Robock A, et al. The representation of snow in land surface schemes: results from PILPS 2 (d). J Hydrometeorol. 2001;2(1):7–25.
150. Slater AG, Barrett AP, Clark MP, Lundquist JD, Raleigh MS. Uncertainty in seasonal snow reconstruction: relative impacts of model forcing and image availability. Adv Water Resour. 2013;55:165–77.
151. Smyth EJ, Raleigh MS, Small EE. Particle filter data assimilation of monthly snow depth observations improves estimation of snow density and SWE. Water Resour Res. 2019;55(2):1296–311.
152. Strozzi T, Matzler C. Backscattering measurements of alpine snowcovers at 5.3 and 35 GHz. IEEE Trans Geosci Remote Sens. 1998;36(3):838–48.
153. Sturm M, Goldstein MA, Parr C. Water and life from snow: a trillion dollar science question. Water Resour Res. 2017;53(5): 3534–44.

154. Su H, Yang ZL, Niu GY, Dickinson RE. Enhancing the estimation of continental-scale snow water equivalent by assimilating MODIS snow cover with the ensemble Kalman filter. J Geophys Res-Atmos. 2008;113(D8).
155. Sun SF, Xue YK. Implementing a new snow scheme in simplified simple biosphere model. Adv Atmos Sci. 2001;18(3):335–54.
156. Sun C, Walker JP, Houser PR. A methodology for snow data assimilation in a land surface model. J Geophys Res-Atmos. 2004;109(D8).
157. Tachiiri K, Shinoda M, Klinkenberg B, Morinaga Y. Assessing Mongolian snow disaster risk using livestock and satellite data. J Arid Environ. 2008;72(12):2251–63.
158. Tapley BD, Bettadpur S, Ries JC, Thompson PF, Watkins MM. GRACE measurements of mass variability in the earth system. Science. 2004;305(5683):503–5.
159. Tarboton D, Bloschl G, Cooley K, Kimbauer R, Luce C. Spatial snow cover processes at Kiihtai and Reynolds Creek. Spatial Patterns in Catchment Hydrology. Observations and Modelling. 2001;158.
160. Tedesco M. Remote sensing of the cryosphere: Wiley; 2014.
161. Tedesco M, Pulliainen J, Takala M, Hallikainen M, Pampaloni P. Artificial neural network-based techniques for the retrieval of SWE and snow depth from SSM/I data. Remote Sens Environ. 2004;90(1):76–85.
162. Tedesco M, Derksen C, Pulliainen J. Hemispheric snow water equivalent: the need for a synergistic approach. EOS, Transactions American Geophysical Union. 2012;93(31):305–305.
163. Thirel G, Salamon P, Burek P, Kalas M. Assimilation of MODIS snow cover area data in a distributed hydrological model using the particle filter. Remote Sens. 2013;5(11):5825–50.
164. Toure A, Reichle R, Forman B, Getirana A, De Lannoy G. Assimilation of MODIS snow cover fraction observations into the NASA catchment land surface model. Remote Sens. 2018;10(2):316.
165. Trujillo E, Molotch NP, Goulden ML, Kelly AE, Bales RC. Elevation-dependent influence of snow accumulation on forest greening. Nat Geosci. 2012;5(10):705–9.
166. Viviroli D, Dürr HH, Messerli B, Meybeck M, Weingartner R. Mountains of the world, water towers for humanity: typology, mapping, and global significance. Water Resour Res. 2007;43(7).
167. Walter MT, Brooks ES, McCool DK, King LG, Molnau M, Boll J. Process-based snowmelt modeling: does it require more input data than temperature-index modeling? J Hydrol. 2005;300(1–4):65–75.
168. Wiesmann A, Mätzler C. Microwave emission model of layered snowpacks. Remote Sens Environ. 1999;70(3):307–16.
169. Wu X, Che T, Li X, Wang N, Yang X. Slower snowmelt in spring along with climate warming across the northern hemisphere. Geophys Res Lett. 2018;45(22):12–331.
170. Xu L, Dirmeyer P. Snow-atmosphere coupling strength in a global atmospheric model. Geophys Res Lett. 2011;38(13).
171. Xu L, Dirmeyer P. Snow–atmosphere coupling strength. Part I: effect of model biases. J Hydrometeorol. 2013;14(2):389–403.
172. Zhao L, Yang ZL. Multi-sensor land data assimilation: toward a robust global soil moisture and snow estimation. Remote Sens Environ. 2018;216:13–27.
173. Zsoter E, Cloke H, Stephens E, de Rosnay P, Muñoz-Sabater J, Prudhomme C, et al. How well do operational numerical weather prediction configurations represent hydrology? J Hydrometeorol. 2019;20(8):1533–52.